Advancements in Satellite and AI Technologies for Methane Detection

Introducing MethaneDART: A Scalable Platform for Methane Intelligence

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Topics Covered

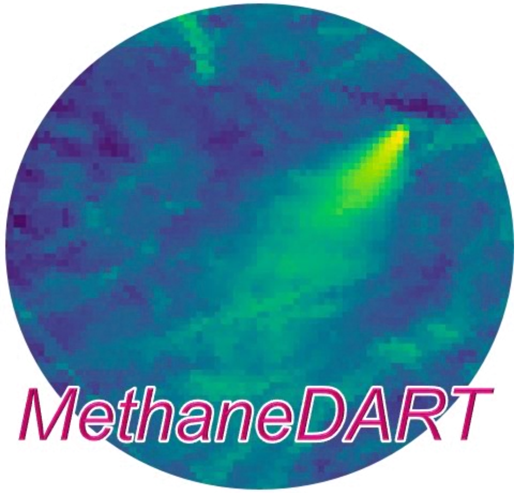
1. Introduction – The *MethaneDART* project and team
2. Scaling Methane Detection for Proactive Leak Mitigation
3. Addressing Methane Monitoring's Big Problem
4. *MethaneDART's* Core Technology
5. *MethaneDART* Modeling Results
6. Web Application Prototype

MethaneDART: The Methane Emissions Detection, Analysis, and Resource Management Tool

We created *MethaneDART* to meet the growing need for faster methane detection that accelerates leak response, keeps natural gas out of the atmosphere & saves operators time, money.

NOAA TECHNOLOGY PARTNERSHIPS OFFICE

- Funded through Phase-1 SBIR-STTR NOAA Grant
- 6-month project
- Phase-II proposal submitted (2 years of funding)



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The Team

Jon Prehn
- UI/UX
- Software Development

Daniel Rodriguez
- Atmospheric Chemistry
- Market Research

Carl Talsma
- PI, Project Management
- AI / Machine Learning

Yunha Lee, PhD
- Physical Plume Modeling
- AI / Machine Learning

Kelly Graham, PhD
- AI / Machine Learning
- Plume Modeling

BJ Brooks, PhD
- Satellite Imagery
- Commercialization / Business

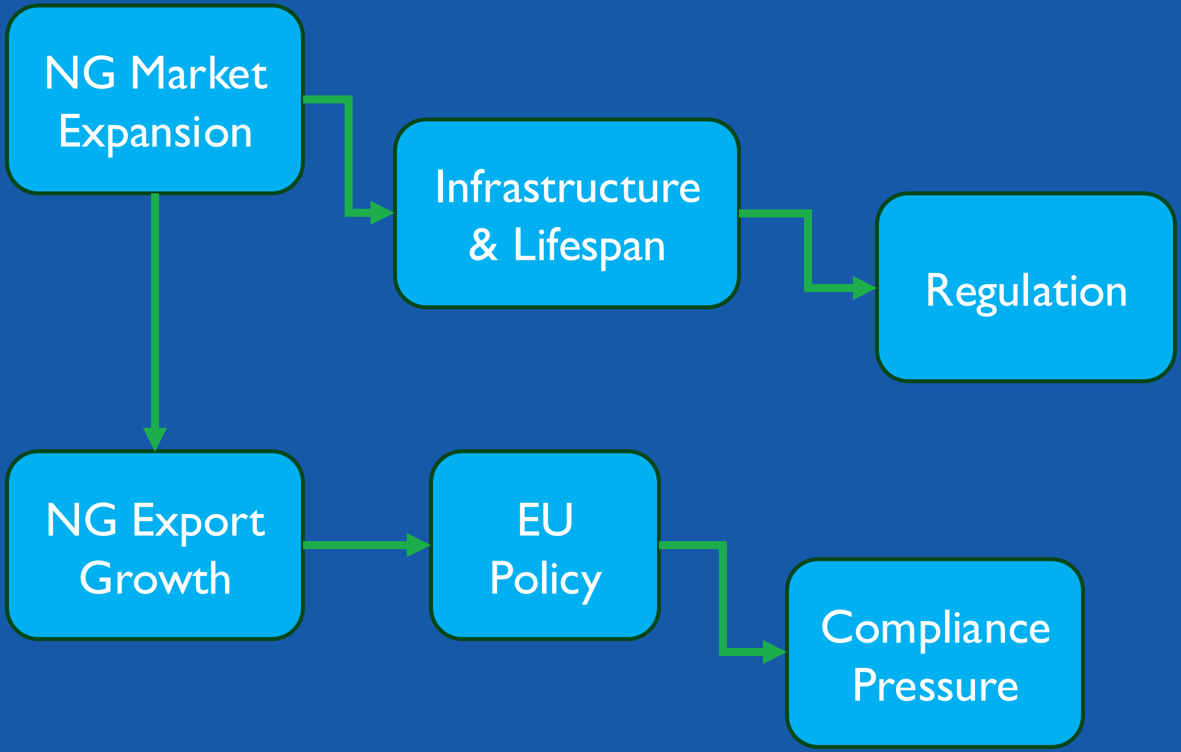
Scaling Methane Detection for Proactive Leak Mitigation

Why MethaneDART?

Because detection is only useful if it leads to action.

The Market Demand for Satellite-Based Methane Leak Detection

What's driving demand for methane detection?



We conducted interviews with operators, conservation groups, and regulators. Here's what we consistently heard

What They Need

in a methane monitoring system

- **Fast detection times** to meet compliance deadlines
- High spatial resolution for **pinpointing leaks**
- Workflow **integration** with existing GIS and leak response tools
- Minimize false positive to avoid unnecessary field deployments
- Cost-effectiveness

Why It's Hard

- Infrastructure is often in remote locations & imaging the entire Earth takes a long time!
- Often numerous operators occupy the same field in close proximity
- Higher spatial resolution comes at the expense of **longer revisit times**
- High-accuracy satellite imagery is very **expensive**

photo credits: fguardians.org and RG72

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Regulatory Landscape – The Pressures Operators Face

- Operators must comply with a rapidly evolving methane regulatory landscape
- State Regulations – Stricter methane limits in Colorado, New Mexico, California
- Risk of **Lost Market Access** – EU markets require a low methane intensity (and therefore thorough monitoring)
- EPA NSPS (New Source Performance Standards) – **Leak monitoring and repair mandates**
- EPA WEC (Waste Emissions Charge) paused*, but future regulation remains a focus

photo credits: dvidshub.net and Ken Hodge

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Addressing Methane Monitoring’s Big Problems

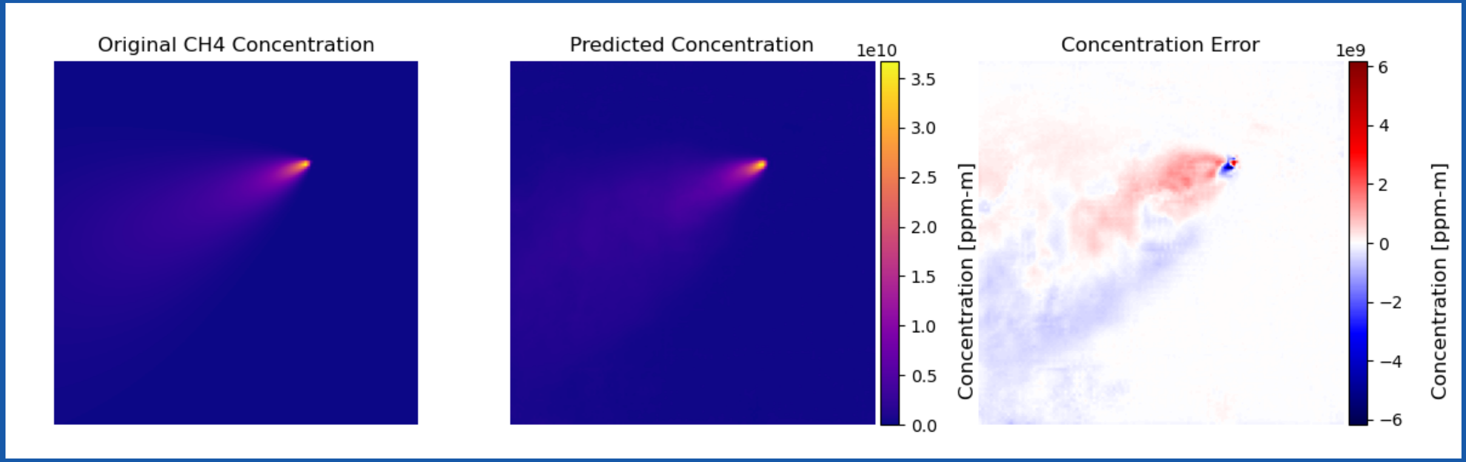
A Scalable, cross-sector approach is needed to fill the gap

Where Today's Tools Excel – and Where Gaps Remain

- Tradeoffs: Existing methane detection solutions face tradeoffs in speed, cost, and spatial coverage.
  - Fixed sensors: Enable continuous monitoring at specific points, but **widespread deployment** across pipeline networks can be cost-prohibitive.
  - Aerial & drone surveys: Provide high-resolution data, though they can be **cost-intensive** and episodic in coverage.
  - CarbonMapper (3/30-day **latency**): Offers valuable regional insights, but latency may limit operational responsiveness.

MethaneDART: Accelerating Detection, Enabling Action

- Rapid, 1-day latency* in detection supports **timely field response**
- Targeting high-resolution, **leak-level precision**, enhance accuracy
- **Workflow-ready design** integrates seamlessly with GIS platforms
- **Phased rollout**: early adopters (2025–2027), commercial launch (2027), global scaling (2028+)



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Why Now?

Regulation of methane is on the rise

Public visibility is on the rise

Monitoring tech is ready and capable

Stakeholders are aligned

→ *MethaneDART is built to meet this opportunity.*

MethaneDART's Core Technology

Applied AI + Remote Sensing for Methane

The Satellite Data Landscape for Methane Detection

Dataset	Spatial Resolution	Return Period	SWIR Bands	Detection Threshold CH_4	Coverage	Availability
TROPOMI Sentinel-5 precursor	5 km	16 days	2 bands	4200 (kg/hr)	Near-polar	Public
Greenhouse gas observing satellite (GOSAT)	0.5-10.5 km	3 days	3 bands	7100 (kg/hr)	Global	Public
GOSAT-2	0.5-10.5 km	6 days	5 bands	4000 (kg/hr)	Global	Public
MethaneSAT	.1 x .4 km	3-4 days	Direct CH_4 product	2 (ppb)	Global	Public
GHGSAT	25 m	14 days	Direct CH_4 product	1000 (kg/hr)	Global	Proprietary (may be available through ESA)
Prisma	30 m	29 days (task based)	Hyperspectral (9 nm)	500-2000 kg/hr	Global	Public
EnMAP	30 m	27 days	Hyperspectral (10 nm)	100-500 kg/hr	Global	Public (Scientific Use)
Tanager-1	30 m	7 days	Hyperspectral (5 nm)	90 kg/hr	Global	Private (paid product)
Landsat 8	30 m	16 days	2 bands	1000 kg/hr	Global	Public
WorldView-3	30 cm	1-3 days (task based)	8 bands	<100 kg/hr	Global	Private (paid product)
EMIT	62 m	~5 days (irregular orbit, ISS)	Hyperspectral (7.4 nm)	200 kg/hr	Global	Public
Sentinel-2	60 m	3-5 days	3 Bands	1000 kg/hr	Global	Public

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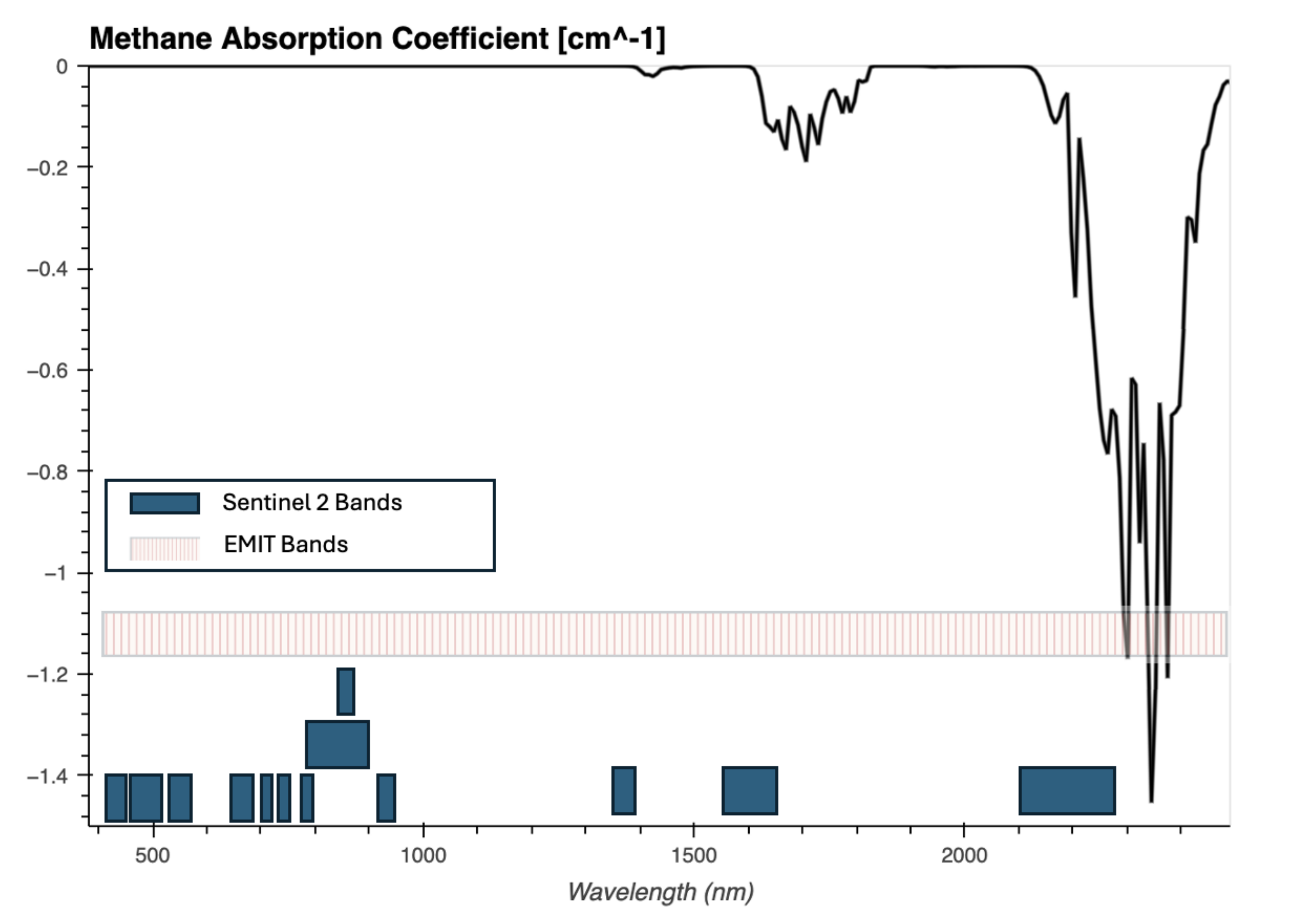
Satellite Data: Sentinel-2 and EMIT

EMIT:
- 285 Spectral Bands (we use 26 bands)
- 60 meter spatial resolution
- ~3 day revisit time (irregular

Sentinel-2:
- 13 Spectral Bands (we use 3 important for CH_4)
- 60 meter spatial resolution
- 2-5 day revisit time depending on latitude



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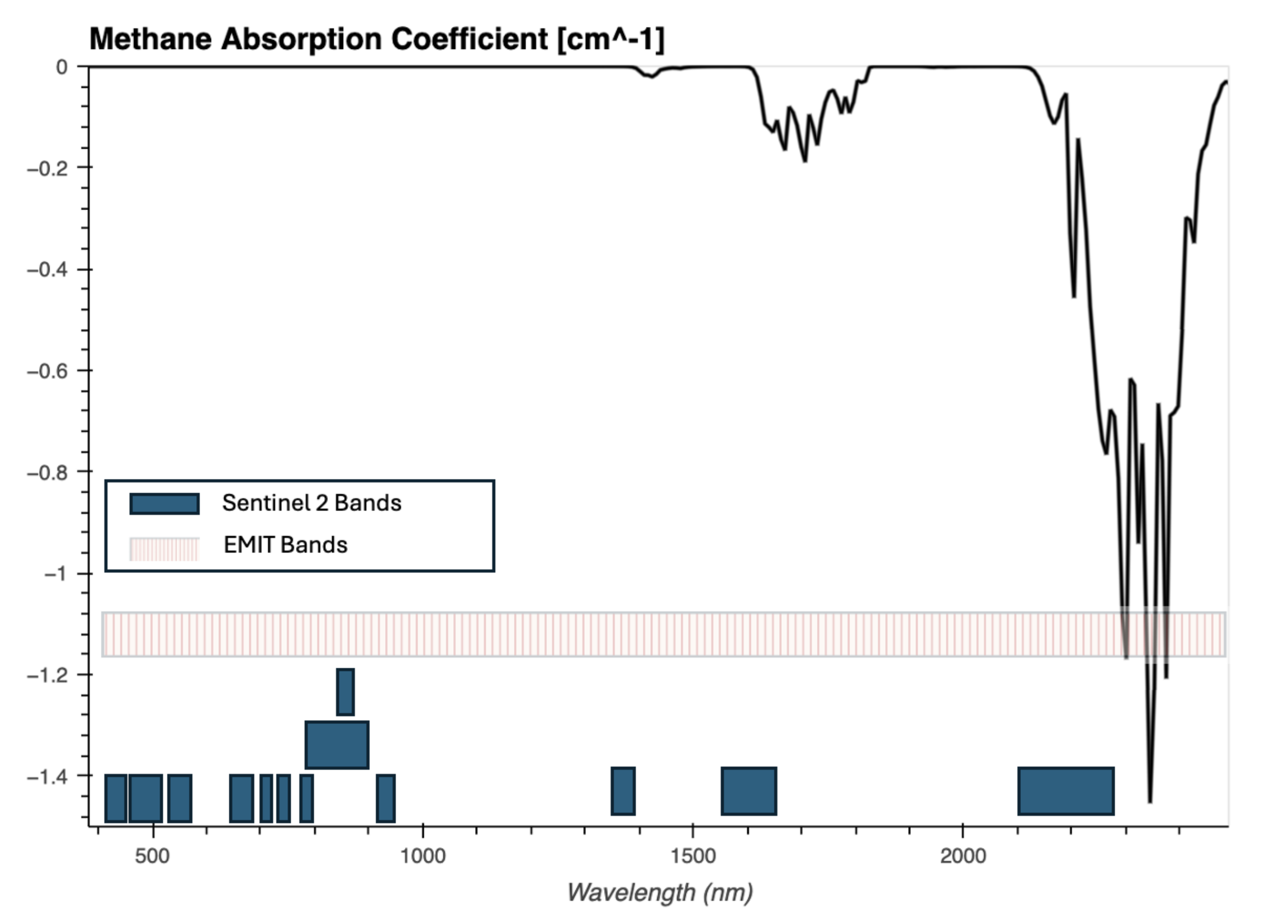
Inferring Plume Characteristics

- Beer Lambert Law

$$A = \varepsilon c l$$

A	Absorbance	
ε	Molar absorption coefficient	$M^{-1}cm^{-1}$
c	Molar concentration	M
l	optical path length	cm

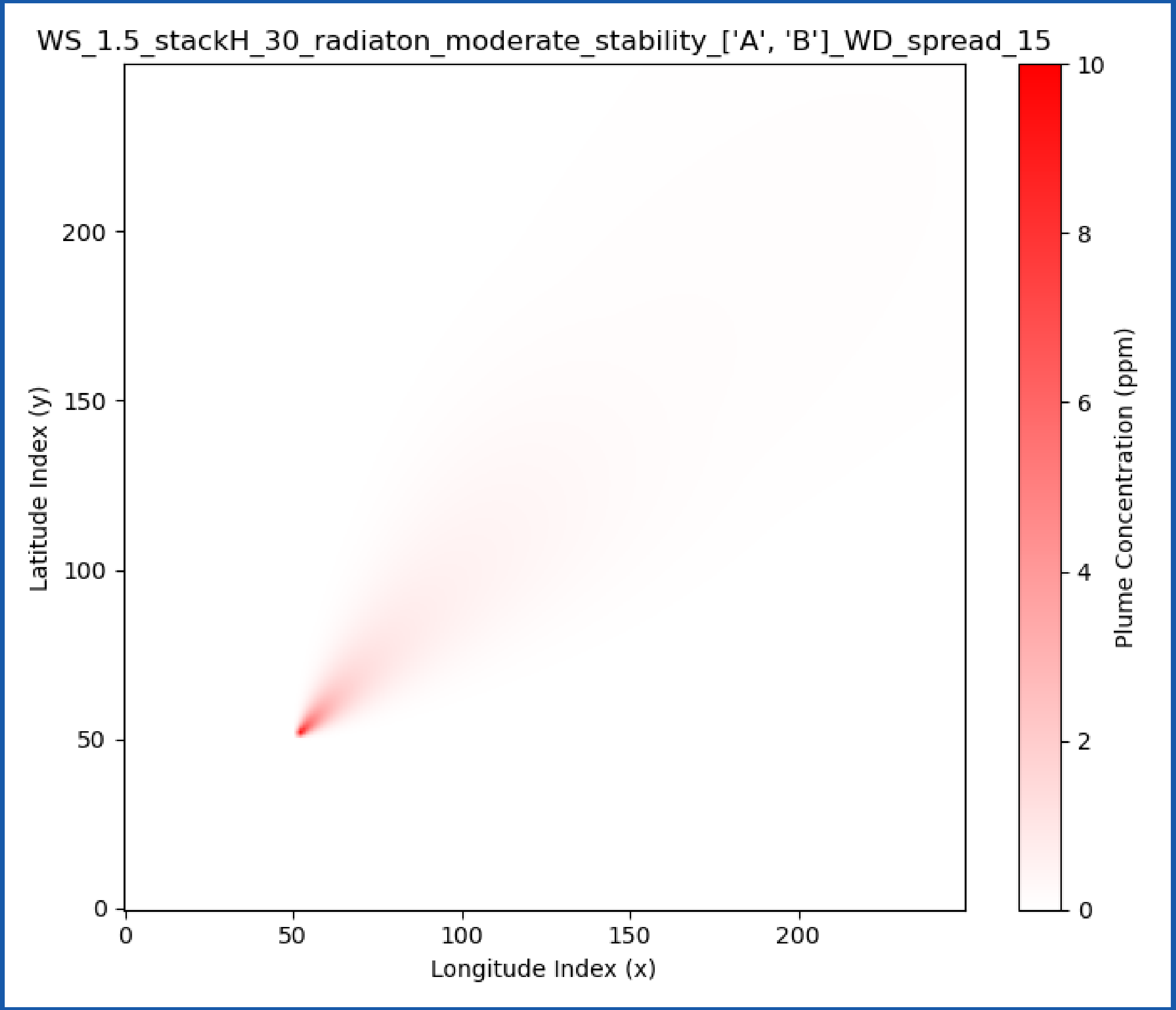
- Knowing the spectral characteristics of CH_4 allows us to simulate how CH_4 plumes will appear in satellite imagery



Gaussian Plume Model

- Plumes simulated using a wide range of conditions
  - Wind Speed
  - Atmospheric Stability
  - Spread Coefficient
  - Radiation

- 54 individual plumes created
- Wind Direction (random)
- Emissions Rate (100 - 70,000 kg/hr)



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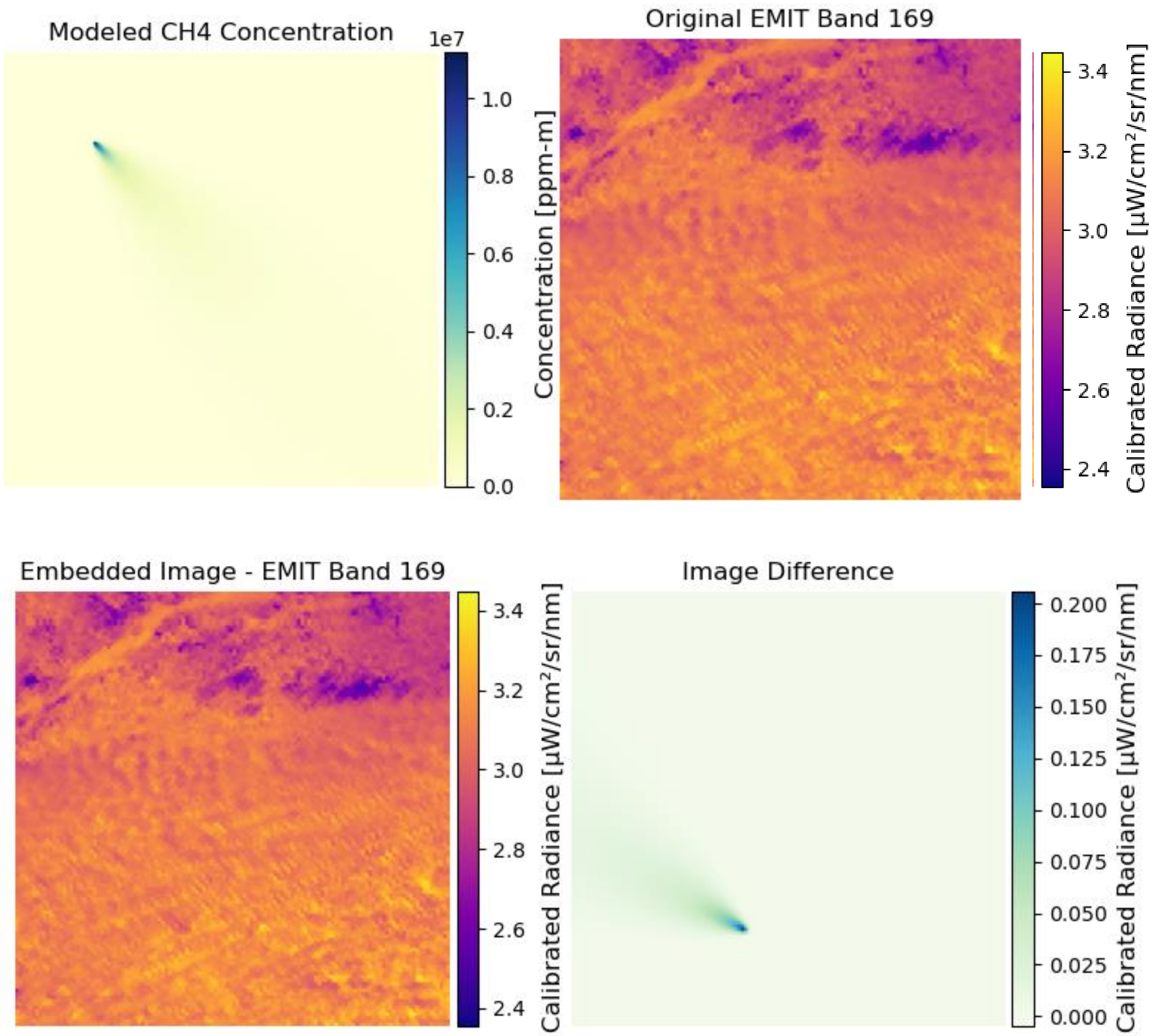
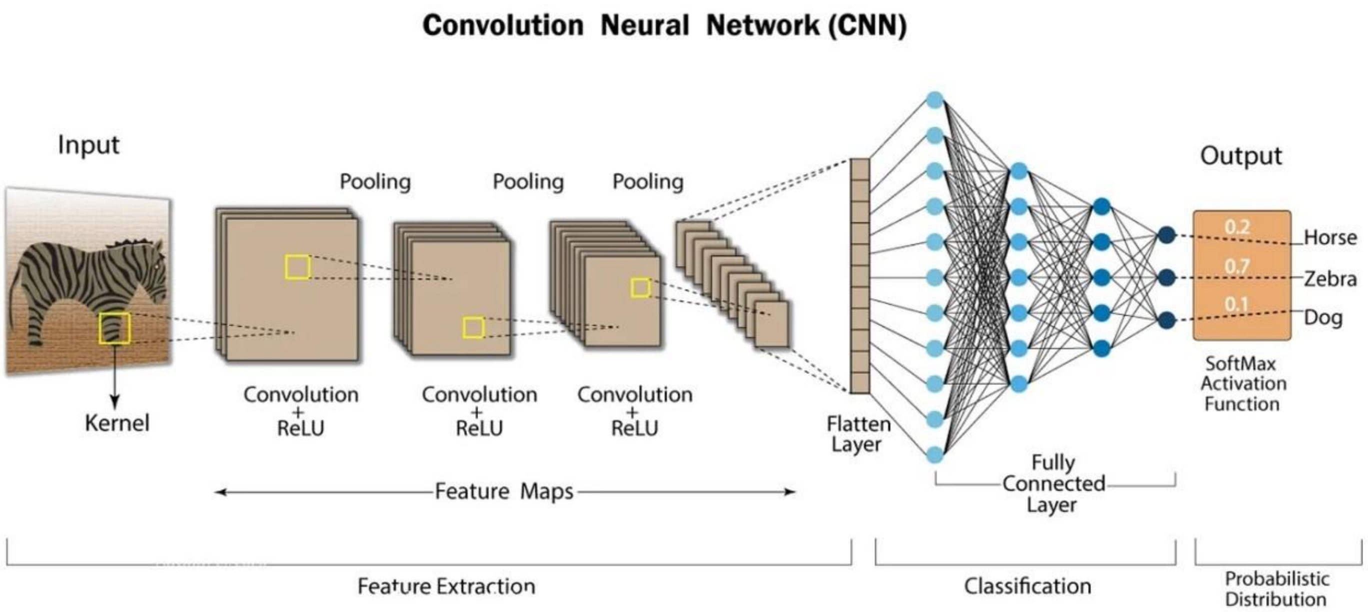
Embedding the Plumes

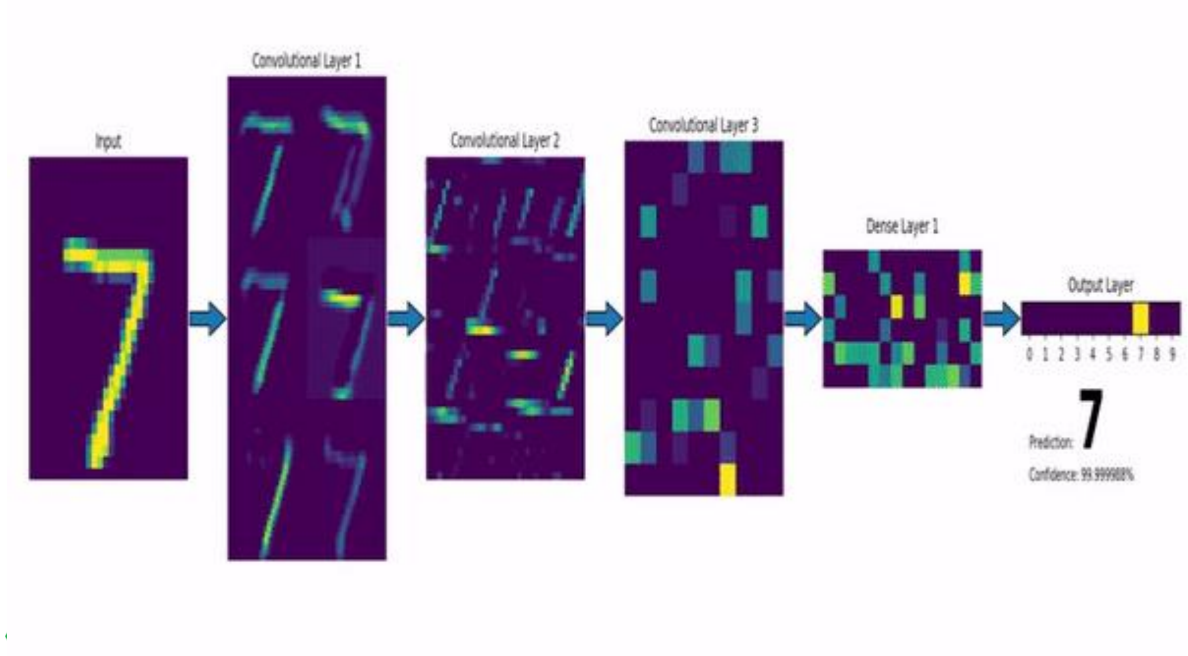
- Plume is placed in a random location and random orientation (wind direction)
- Use Beer Lambert law to calculate additional absorption from CH_4
- Only use locations where we expect no other CH_4 emissions
- ~300 images collected
- Create a training dataset of 2000 embedding plume images

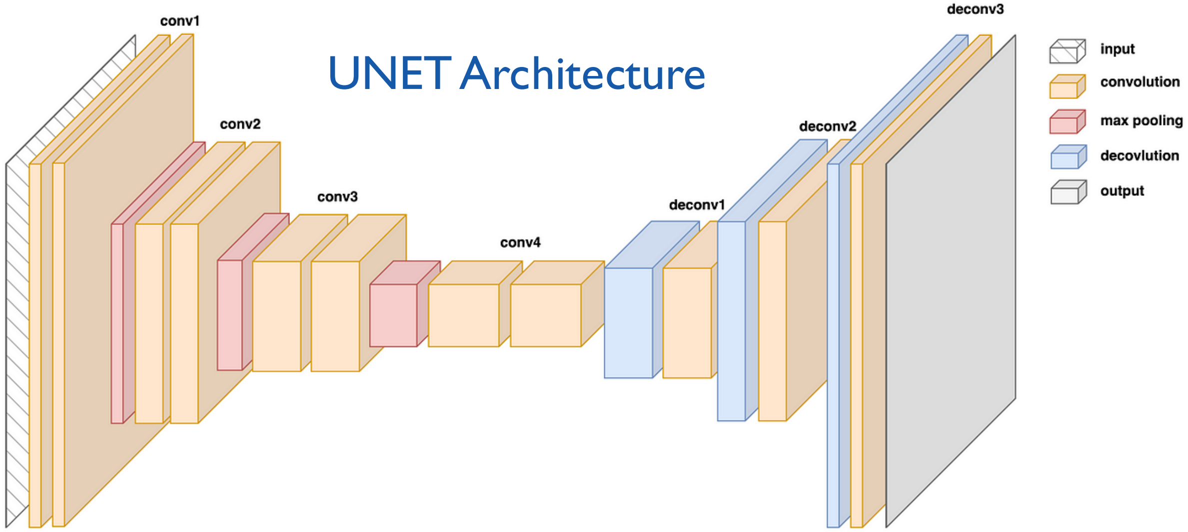


UNET Architecture

- UNET's are popular for image identifications.
- Convolution layers uses multiple filter/kernels to slide over an image to create a feature map output.
- UNET applications use an encoder/decoder architecture to identify feature and then reconstruct an image using those features

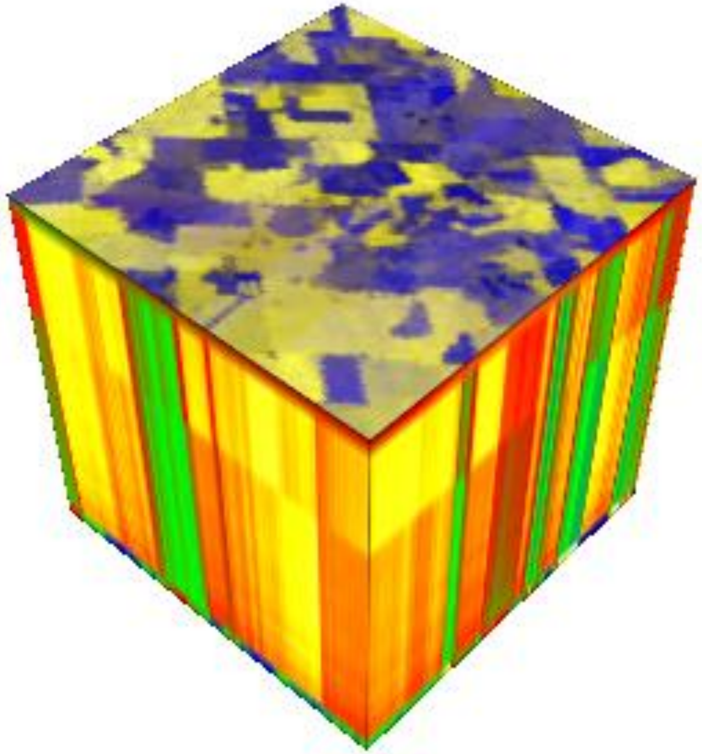




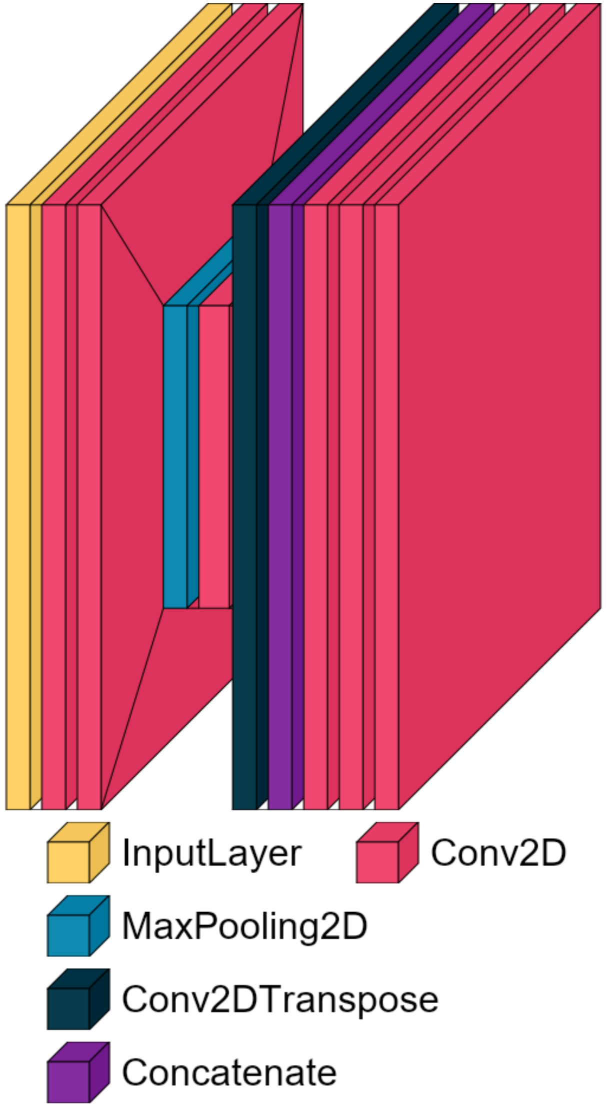


Machine Learning & Model Inversion

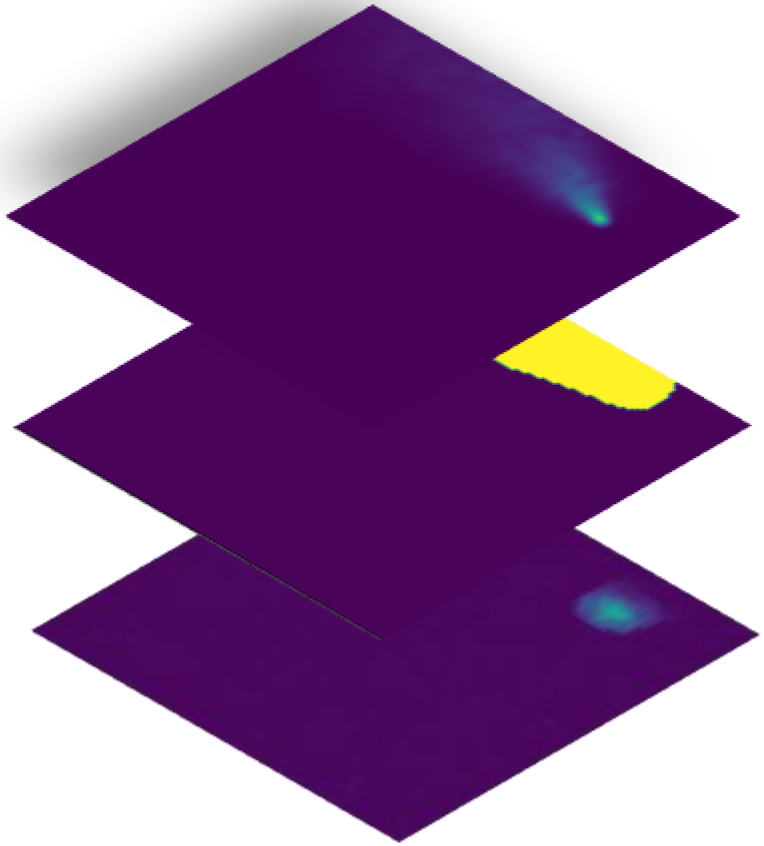
Input:
EMIT Satellite Data
[128 x 128 x 28 bands]
x ~2000 images



UNET Neural Network



Output:
Inferred CH_4 Plume Concentration,
Segmentation, & Location



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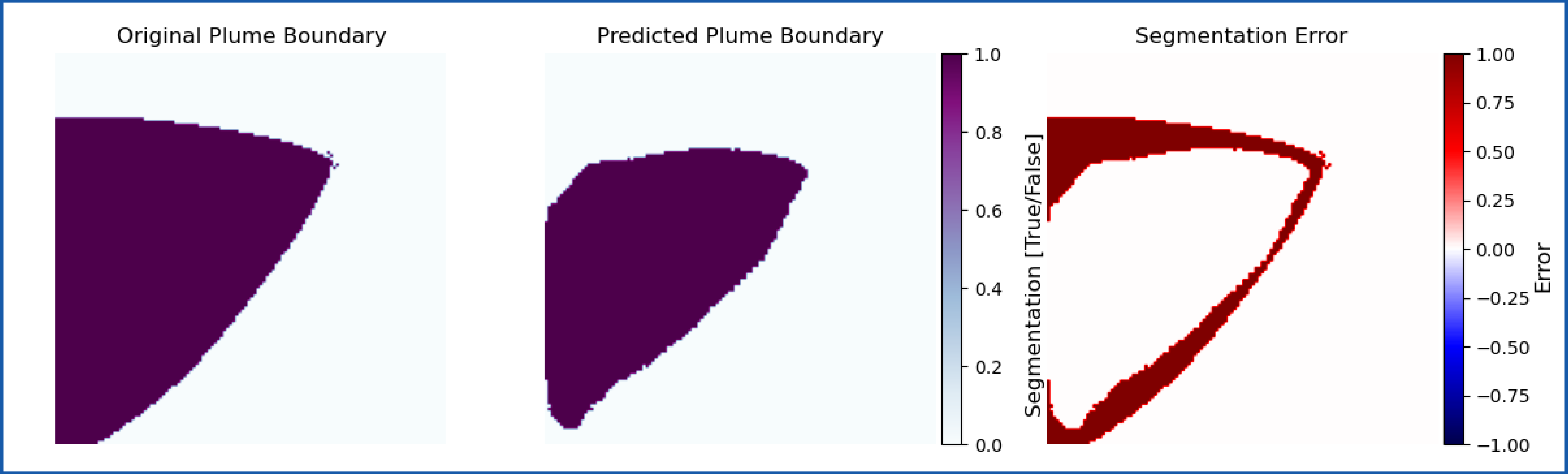
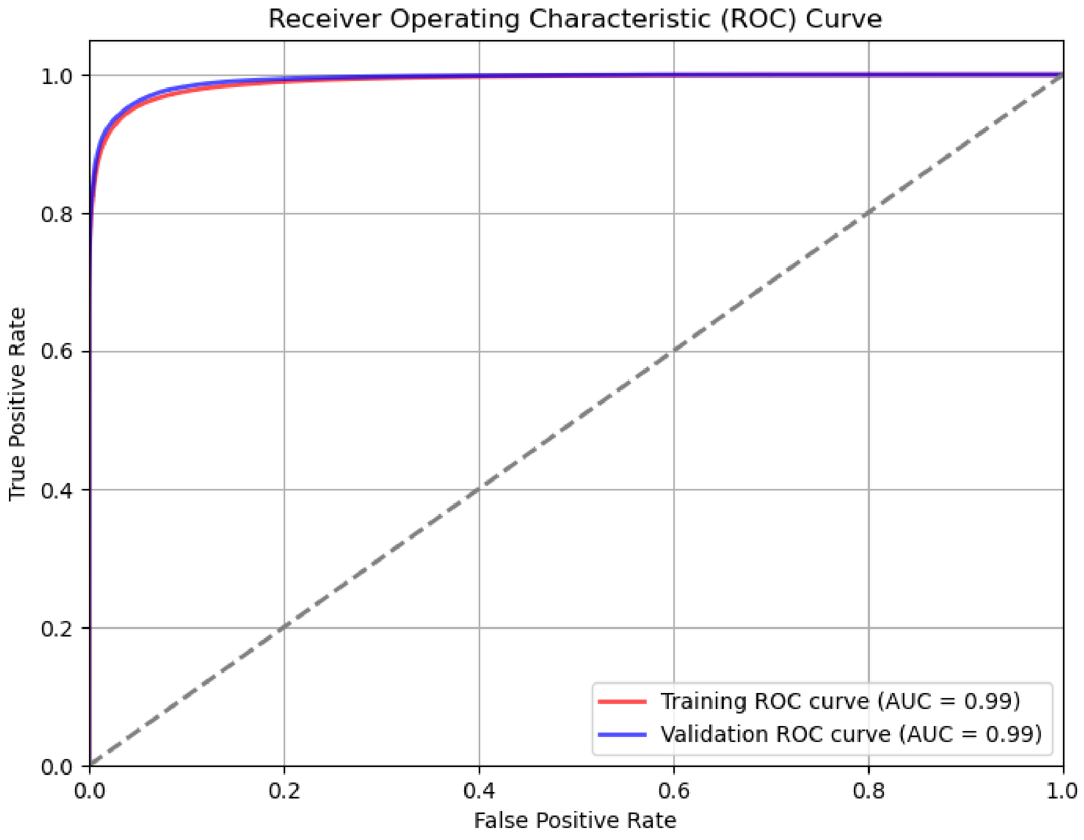
MethaneDART Modeling Results

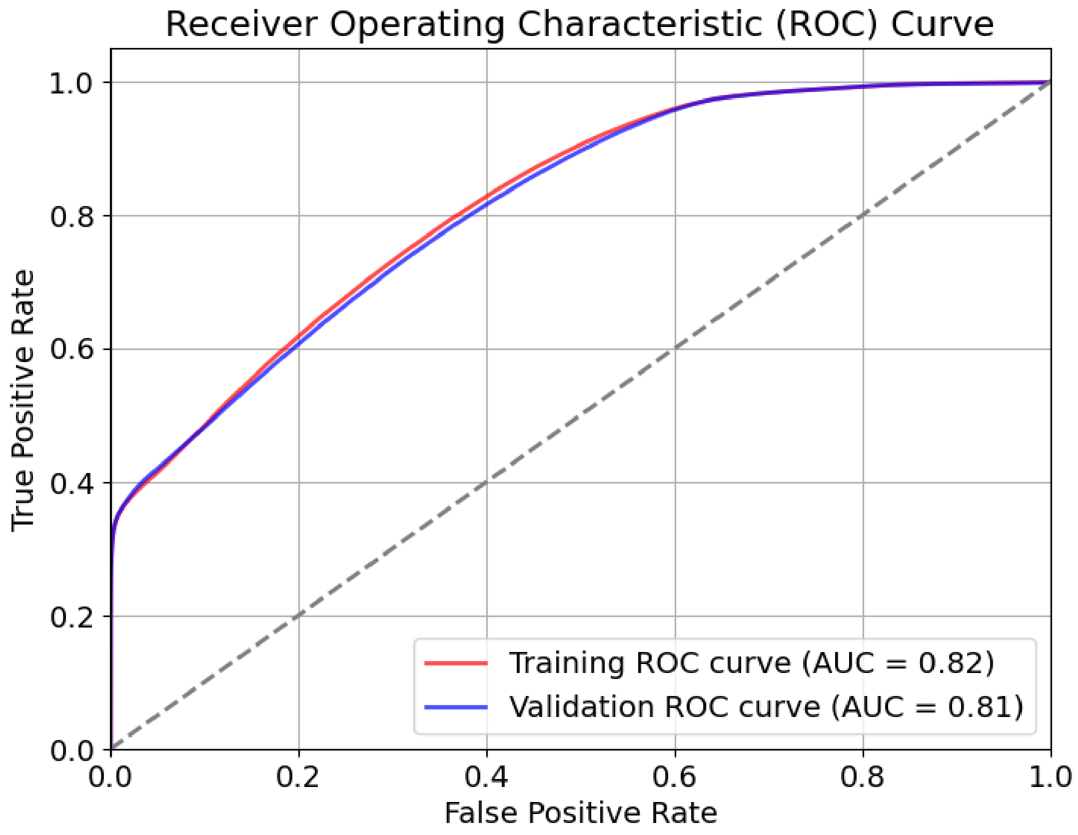
Model Performance and Real-World Applications

Machine Learning Results: Plume Segmentation

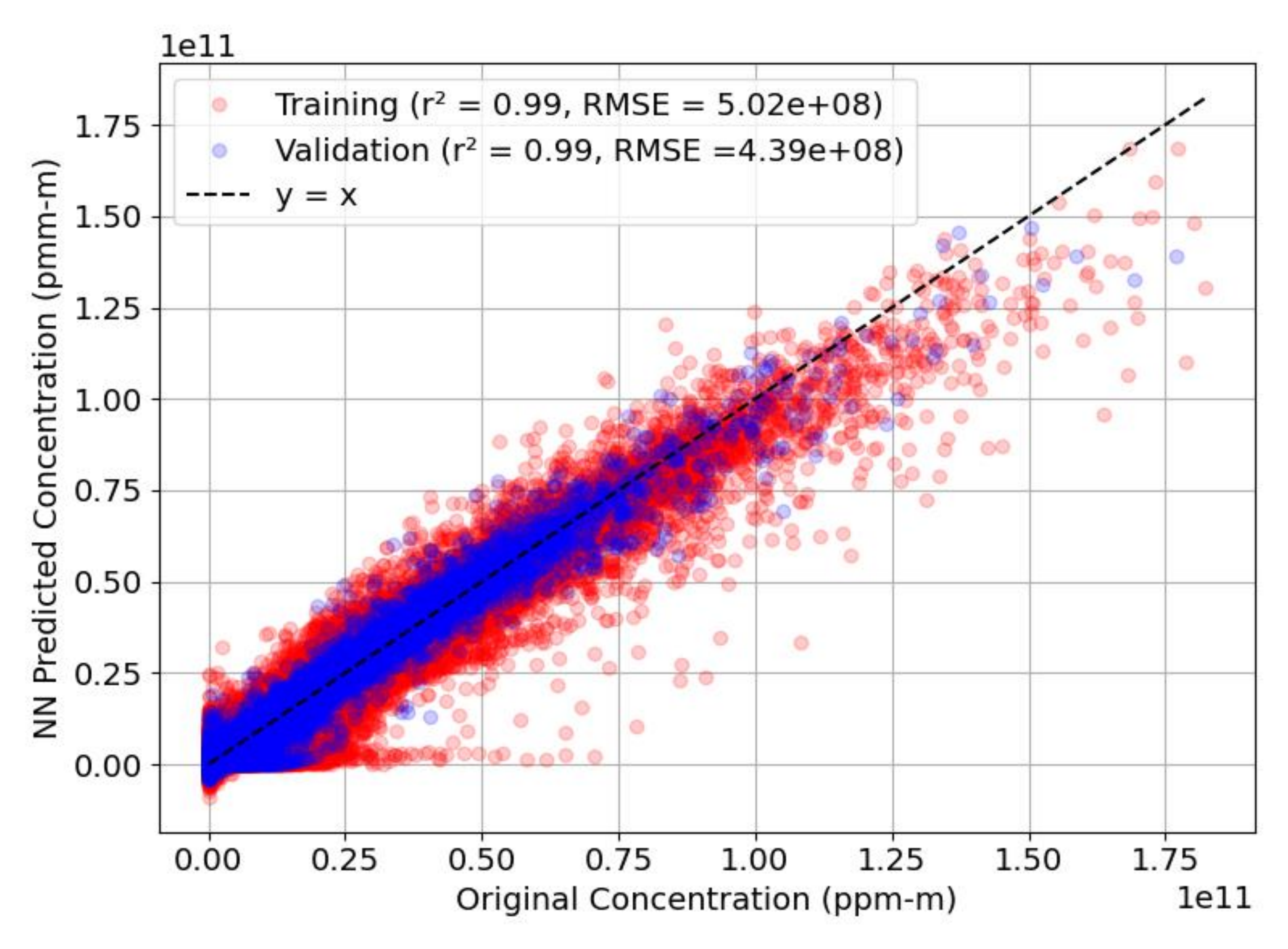


Machine Learning Results: Plume Segmentation





Machine Learning Results: Methane Concentration



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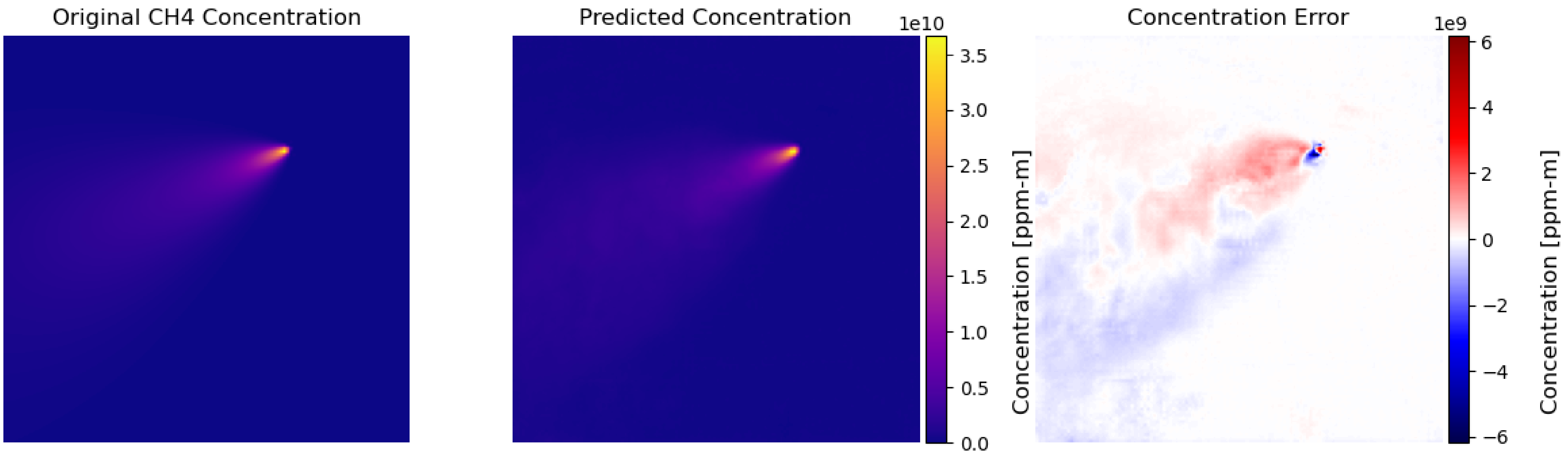
Machine Learning Results: Methane Concentrations



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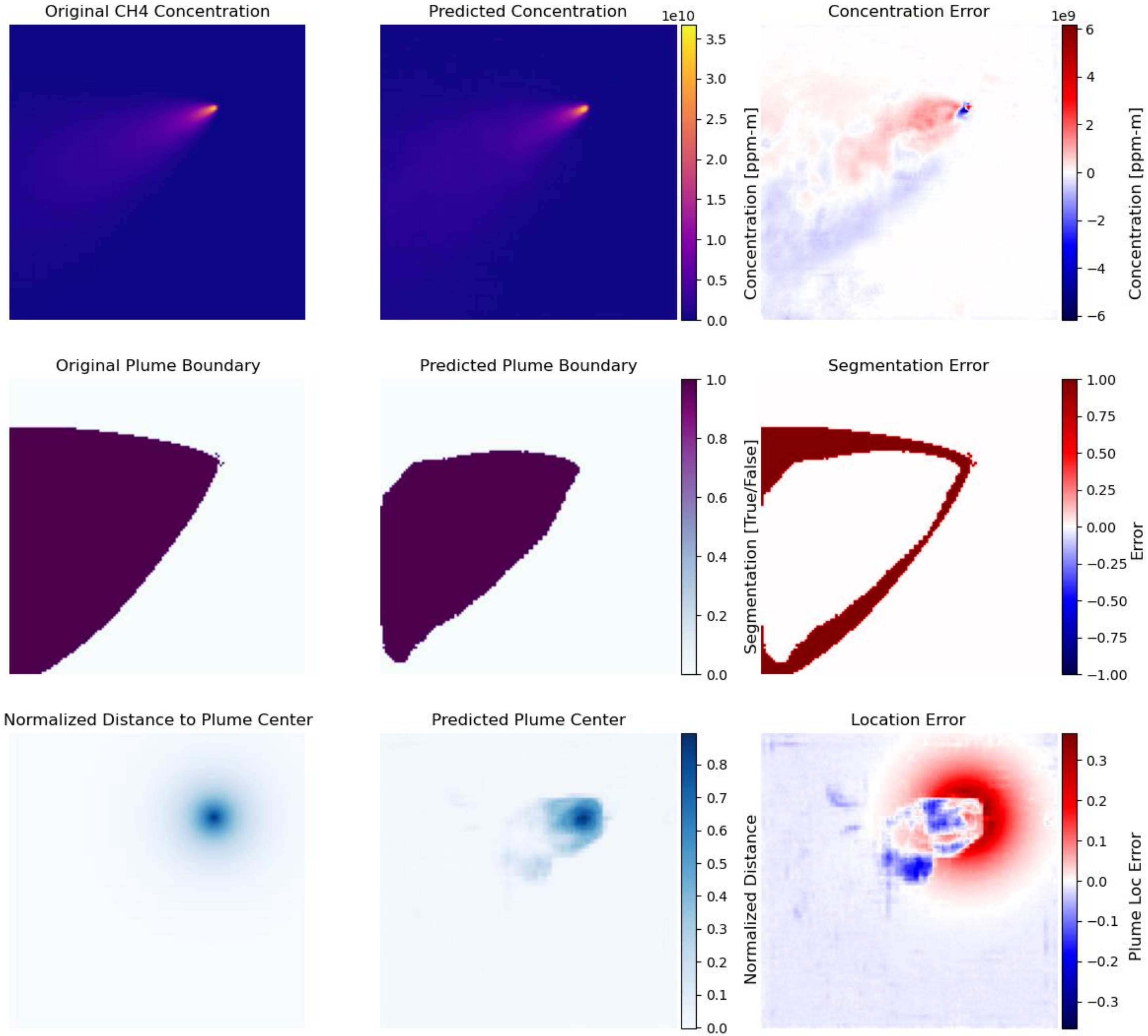
Machine Learning Results



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Machine Learning Results

Emissions Rate

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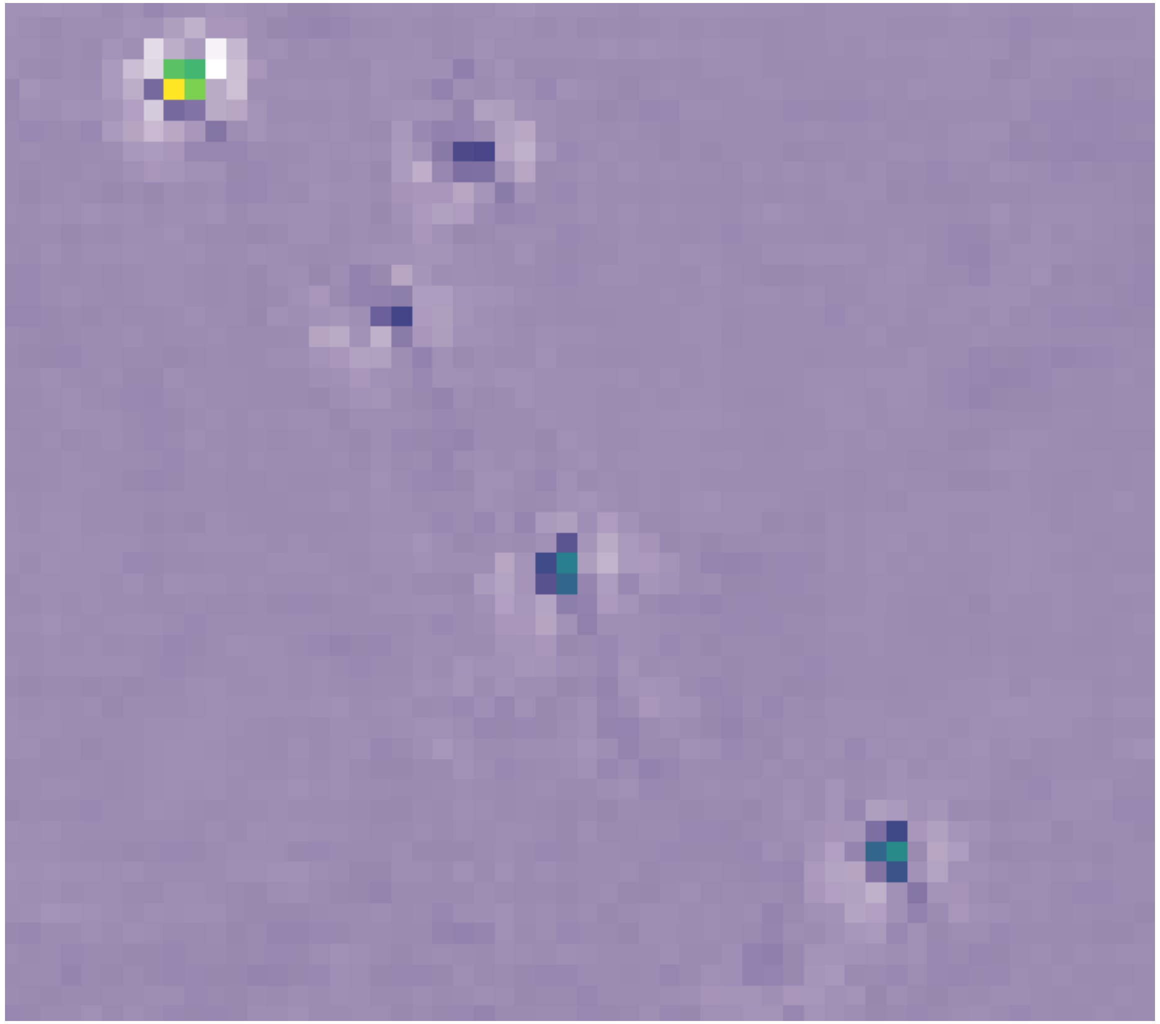
Machine Learning Results



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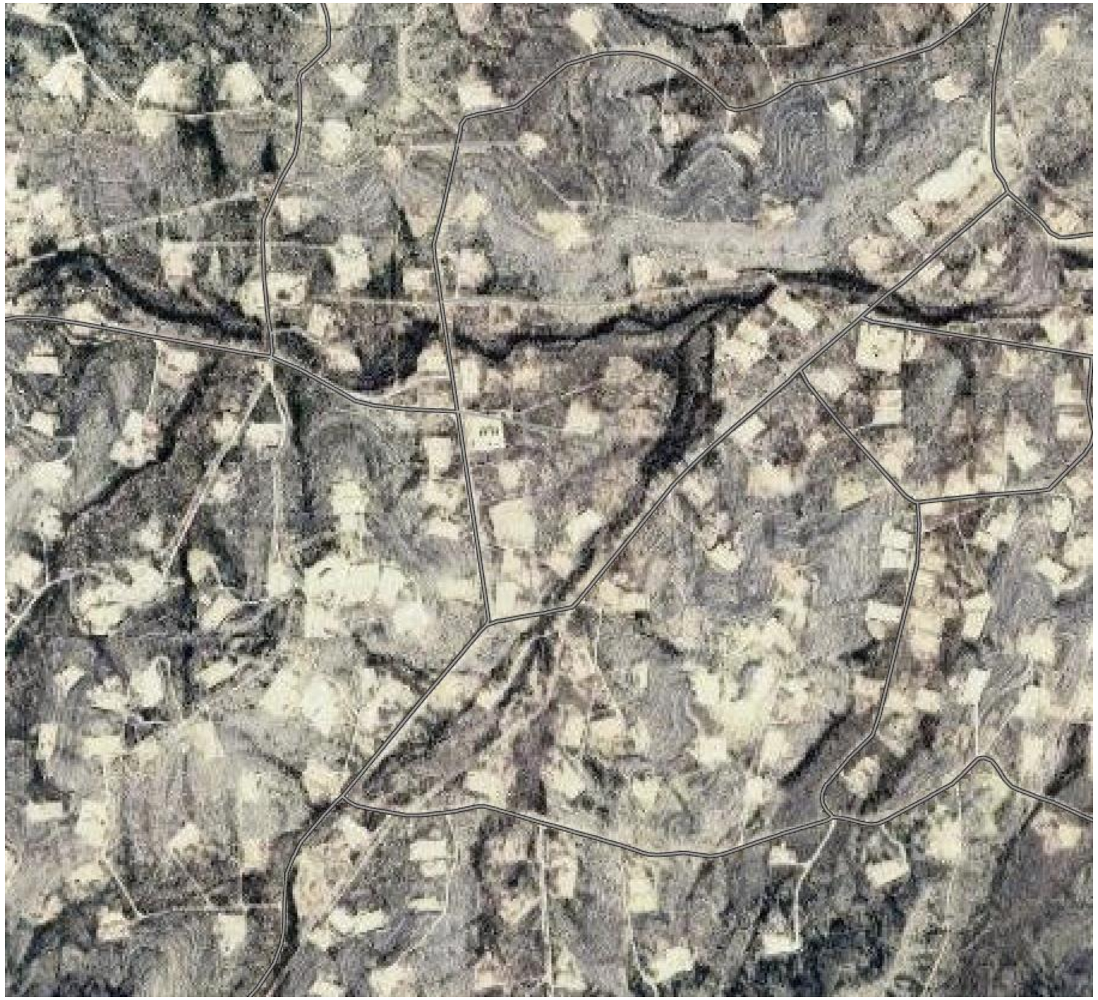
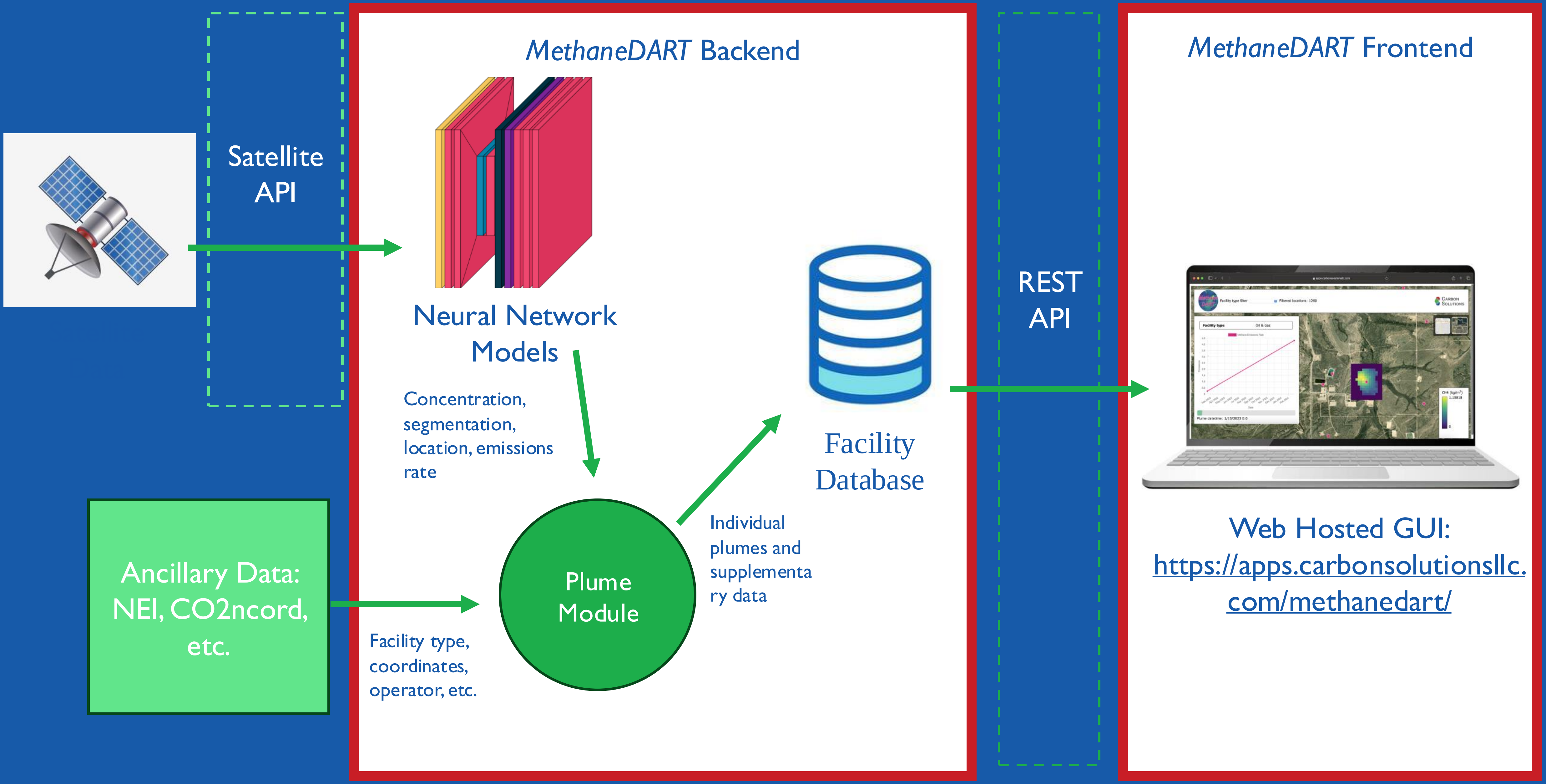
Validating Model Results in the Real World

- Ran the model on known plume locations from reported datasets and publicly reported plumes
- Identified ~1260 plumes
- Heuristics and thresholding for plume definitions, extents, etc.
- Validation require real world point source emissions
- Controlled Release Experiments




Satellite API
MethaneDART Backend
Neural Network Models
Concentration, segmentation, location, emissions rate
Facility Database
Individual plumes and supplementary data
Plume Module
Ancillary Data: NEI, CO2ncord, etc.
Facility type, coordinates, operator, etc.
REST API
MethaneDART Frontend
Web Hosted GUI:
https://apps.carbonsolutionsllc.com/methanedart/

Thank You!

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